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# RANKING SYSTEMIC RISKS IN BANK NETWORKS

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# RANKING SYSTEMIC RISKS IN BANK NETWORKS

*Research-in-Progress*

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## Abstract

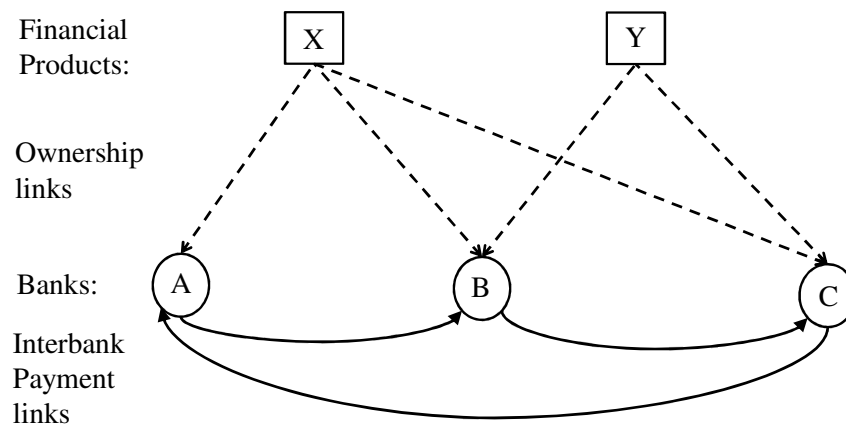
*The recent global financial tsunami (2007 – present) has swiped the whole world with disastrous consequences, leading to the bankruptcy of major banks, trillions of dollars in economic rescues, and major national economic failures. Unlike previous financial crisis, one major driver of this crisis is the contagious failures of banks through a network of interbank payments and correlated bank portfolios of financial products. The risk that the failure of a single bank can cause a cascading failure of other connected banks and may potentially bring down the entire banking system (network), is defined as systemic risk. Existing bank risk management research focused on the causes and impacts of systemic risk but largely ignored the monitoring and preventive mechanism. In this study, we developed a network-based algorithm to rank systemic risk of banks and financial products in the bank network. In addition, we extended the network model of banking system developed in previous systemic risk research and adopted this model in the evaluation experiment of our proposed algorithm. This algorithm may provide an effective mechanism for stakeholders in the banking industry to monitor and reduce systemic risk and thereby prevent system-wide breakdown in bank networks.*

**Keywords:** Contagious Bank Failure, System Risks, Ranking Algorithm, Network Analysis

## Introduction

The recent global financial tsunami (2007 – present) has been considered by many economists as the worst financial crisis since the Great Depression in the 1930s (Bullard et al. 2009; Pendery 2009). It has resulted in the collapse of major financial institutions like Lehman Brothers, downturns of stock markets around the world, and even breakdowns of financial systems in several countries like Greece and Iceland. Although the immediate cause or trigger for this crisis is the burst of the U.S. housing bubble and the following liquidity shortfall of major banks, the mechanism that spreads and magnifies their impacts is the largely interconnected U.S. bank network (Harrington 2009; Markose et al. 2010). In this network, banks are connected with each other through interbank payments and correlated bank portfolios (i.e. owning the same financial product(s) such as IBM stock) (Elsinger et al. 2006). A bank's solvency largely depends on the interbank payments it receives from other banks in the network and the value of its portfolio of financial products. As such, the value of a bank depends on the financial health of the relevant bank network. Therefore, correlation in interbank payments and bank portfolio values can result in contagion of insolvency between banks in this network in a domino effect.

To illustrate how this contagion of insolvency lead to bank failures, Figure 1 shows a simple bank network containing three banks A, B and C, and two financial products (e.g., securities, bonds or financial derivatives) X and Y. A solid line in the figure represents an interbank payment relationship between two banks while a dotted line represents an ownership relationship between a bank and a financial product. We use an out-link to represent an ownership relationship between a bank and a financial product because only the default of a financial product has an impact on an owner bank, not the other way around. Nevertheless, this simple bank network illustrates interbank payment relationships among banks and their interdependencies due to holding of same financial products. As Figure 1 shows, Bank A has a payment relationship with Bank B, and Bank A owns a certain share of Financial Product X. In this network, a contagious failure may happen as followings. A sudden decrease in the market value of financial product X may cause Bank A to default on its payment obligations to Bank B. Such a default along with the decreased value of X may in turn lead Bank B to fail on its payment obligations to Bank C. A default by C may, in turn, have a major feedback effect on A and potentially bankrupt A. This example illustrates the risk of domino collapsing in a banking system, starting with the default of a single bank through a contagious failure process in a bank network. Such type of risk is often termed as "systemic risk" (Bullard et al. 2009; Markose et al. 2010).



**Figure.1 An Illustration of Bank Network**

In a bank network, systemic risk refers to the risks associated with the interlinkages and interdependencies among banks, where the failure of a single bank or a group of banks can cause a cascading failure of other connected banks, which may potentially bring down the entire banking system (network). However, existing research on banking regulation and monitoring mainly focused on the risk at the level of the individual bank (Elsinger et al. 2006) but largely overlooked the systemic risk. New models and methods that can discover hidden systemic risks in the bank network are needed to prevent the potential buildup of systemic risks that may cause the breakdown of the whole banking system.

Therefore, it is important to take a system-wide and network perspective to model and analyze systemic risks, and devise effective mechanisms to monitor, manage and prevent such type of risks. The main modeling challenge, identified by Elsinger et al. (2006), is to effectively capture the two major sources of systemic risks: 1) correlated bank investment portfolios that may result in simultaneous insolvency of multiple banks due to negative shocks in financial markets; 2) Banks may default on their interbank payments towards other banks and thus cause them to default or even bankrupt triggering a domino effect. Elsinger et al. (2006) improved a network-based interbank payment model proposed in Eisenberg and Noe (2001) and adopted simulation method to study these two sources of systemic risks in Austrian banking system. However, their analysis focused on simulating the system-wide impacts of potential contagious default events on the banks in various stress scenarios. There is a lack of systematic approach to model and analyze the level of systemic risk associated with each bank and financial product in the bank network. Such approach is particular useful for financial regulators and other stakeholders when devising strategies or mechanisms to prevent or mitigate systemic risks. For instance, before or during the breakdown of the banking system, it would be crucial to know which banks to save (inject capital) and which toxic financial assets to deal with first, in order to stabilize the whole banking system and keep its solvency.

To address this problem, first we modified Elsinger's interbank payment model by incorporating the other major source of systemic risk – correlated bank portfolios. Based on this model, we build a bank network model in which nodes are banks and financial products, while links are interbank payment (between banks) and ownership relationships (between banks and financial products). We then develop a network-based algorithm based on the HITS algorithm (Kleinberg 1999) to model and rank the systemic risk associated with each bank and financial product. At last, we propose to use simulation methods to evaluate the effectiveness of our ranking algorithm in future research. We plan to simulate different stress scenarios using real-world data on the U.S. banking system.

We claim three contributions in this research. Firstly, based on Elsinger's interbank payment model, we developed a bank network model which incorporates the interrelationships between banks and financial products they own. This model better represents the real-world banking system and provides the basis for studying systemic risks associated with correlated portfolios of financial products. Secondly, we developed a network-based ranking algorithm that can be used to rank banks according their systemic risks. This information is useful to bank regulators that need to make decisions on what banks to save first in order to prevent a possible system-wide breakdown. The ranking result can also help individual banks to identify financial products associated with high systemic risks that may has significant negative impacts on their investment portfolios during financial crisis. Thirdly, this research contributes to the literature of financial risk management by studying systemic financial risks in the banking sector with a network-based approach.

The remainder of this paper is organized as follows. In the next section, we review related studies. The third section introduces a mathematical model of banking system based on Elsinger's interbank payment model (2006). The fourth section describes the proposed network-based ranking algorithm. Then we outline a plan to evaluate the effectiveness of our proposed algorithm using simulation techniques. Finally, we discuss the possible implications and potential contributions of our research.

## **Related Studies**

Our study proposes to use a business intelligence approach for managing systemic risk in the bank networks. In this section, we review relevant studies in business intelligence and bank risk management, as well as the network-based ranking algorithm related to the systemic risk ranking algorithm developed in our research.

### ***Business Intelligence and Bank Risk Management***

Various business Intelligence (BI) techniques have been employed to manage bank risk, mostly focusing on predictions of bank failures. These studies often adopt Artificial Intelligence and data mining techniques on real-world banking data, aiming to discover the causes of bank failures and successfully predict potential failures. These techniques include Neural Networks (NN), Support Vector Machines (SVM), Bayesian Networks (BN), and other common classification algorithms. Tam et al. (1992) has demonstrated the effectiveness of Neural Networks technique in bank failure predictions. A fuzzy support vector machine method for credit risk assessment in banking industry is proposed in Wang et al. (2005). Sarkar and Sriram (2001) have applied Bayesian Networks models for early warning of bank failures. In addition, Data mining methods have also been used in the research about anti-

money laundering (John 2004; Zhongfei et al. 2003). In general, these business intelligence techniques can provide novel insights different from traditional financial risk management techniques for decision makers in the banking industry to achieve better risk measurement, assessment and mitigation.

However, there are mainly two issues for existing research using business intelligence techniques on bank risk management. Firstly, the analyses in these studies mainly focus at the level of individual banks or institutions but largely overlook the systemic risk. Secondly, relevant with the previous issue, the relational (network) data such as interbank payment is rarely studied. Thus network analysis techniques or network-based ranking algorithm is rarely used for bank risk management. Our research aims to address these two issues by 1) adopting a network perspective to model systemic risk associated with interbank payments and correlated bank portfolios, and 2) developing network-based ranking algorithm for systemic risk mitigation in bank networks.

### ***Network-based Ranking Algorithms***

With the fast development of digital communication networks (e.g., World Wide Web) in the past decades, various network-based algorithms have been developed to rank the relative importance of nodes in these networks. For instance, these algorithms are widely adopted in modern web search engines like Google and Yahoo which effectively search and rank the web pages on the World Wide Web. Most of such algorithms utilize the network structural information such as degree (i.e., the number of links a node has) for ranking node importance. Two most widely used algorithms are Google's Pagerank (Brin and Page 1998) and the HITS algorithm developed by Kleinberg (1999). Other network-based ranking algorithms include CLEVER (Chakrabarti et al. 1998) project in IBM, SALSA (Lempel and Moran 2001), as well as TrustRank (Gyöngyi et al. 2004). However, these algorithms are mainly used in information retrieval, but have rarely been used in other areas.

Our systemic risk ranking algorithm is based on the HITS algorithm (Kleinberg 1999) which is designed to rank the importance of individual web pages on the Internet. The HITS algorithm calculates two scores for each webpage—the authority score and the hub score. The authority score measures the value of the content for the web page, while the hub score estimates the value of the web page's links to other pages. Authority and hub scores are defined in terms of one another in a mutual recursion. An authority score is computed as the sum of the scaled hub scores that point to that page. A hub score is the sum of the scaled authority scores of the pages it points to. Both scores for each web page are calculated multiple times and normalized in multiple iterations until they converge.

## **A Network-based Model of Banking System**

In this research, we develop a network-based model of banking system mainly for analyzing systemic risks and evaluating the effectiveness of the proposed ranking algorithm. We use this model along with real-world bank-related data to simulate the impacts of various economic shocks on banks and the financial products they own. We also simulate how the proposed algorithm can be used to reduce contagious failures in the bank network under these shocks. Our model is mainly based on the banking system model developed by Eisenberg and Noe (2001) and extended by Elsinger et al. (2006). We modify it to include the systemic risks originated from the correlated bank portfolios.

Considering a set of  $N = \{1, \dots, N\}$  banks, each bank  $i \in N$  has a value  $e_i$  which represents the value of this bank's total assets. The total value of a bank is the sum of its total assets  $e_i$ , the value of this bank's portfolio of financial products, and the value of all interbank payments it received, minus its interbank payment liabilities towards other banks. If the total value of a bank becomes negative, the bank is insolvent. Therefore, there are three components in the total value of a bank – total assets of the bank, the bank's portfolio of financial products, the interbank payments receivable from other banks or interbank liabilities. We then describe our model of banking system in the following three sub sections.

### ***Correlated Bank Portfolios***

The major difference between our model and the model developed by Elsinger et al. (2006) is the inclusion of the correlated bank portfolio component. Elsinger et al. (2006) identified that one of the major sources of systemic risks is the shared holdings of the same financial product(s) in different bank portfolios, causing correlated changes

in bank portfolio values when the prices of these shared financial products change. For instance, the burst of housing bubble has caused major banks to suffer heavy losses in many asset-backed securities (ABS) they own such as Mortgage Backed Securities (MBS), Collateralized Debt Obligations (CDO) (Krahn and Wilde 2006) and Credit Default Swaps (CDS) (Markose et al. 2010). Such loss in correlated bank portfolios may largely reduce the payment abilities of these banks simultaneously, causing their insolvency. However, Elsinger et al. (2006) did not explicitly include this systemic risk component and evaluate its impacts in their model of banking system.

In our modified model of banking system, we develop and include a correlated bank portfolio component to represent this source of systemic risk. We define  $b_i$  as the value of a bank  $i$ 's investment on a portfolio of financial products  $\mathbf{M} = \{1, \dots, M\}$  on the observation day. This value is calculated as

$$b_i = \sum_{k=1}^M R_k V_{ik}$$

where  $R_k$  is financial product  $k$ 's market closing price at the observation day and  $V_{ik}$  is the volume the bank  $i$  held at the end of that day.

### Interbank Payment

To model interbank payments, we use a  $N \times N$  matrix  $L$ , in which  $L_{ij}$  represents bank  $i$ 's payment obligation towards bank  $j$  and  $N$  represents the set of all banks in the banking system. Therefore, the value of bank  $i$ 's total obligations towards the rest of the banking system can be denoted as  $d_i = \sum_{j=1}^N L_{ij}$ . We then define a new matrix  $\Pi \in [0,1]^{N \times N}$  by normalizing the entries by the total obligation  $d_i$ :

$$\pi_{ij} = \begin{cases} L_{ij} / d_i & \text{if } (d_i > 0) \\ 0 & \text{otherwise} \end{cases}$$

### Clearing Payment Vector

Then the banking system can be described as the sum of the three aforementioned components – total assets  $e$ , correlated bank portfolio  $b$ , and the interbank payment obligations  $d$ . Following Eisenberg and Noe (2001) and Elsinger et al. (2006), we then define a *clearing payment vector*  $p^*$  as

$$p_i^* = \begin{cases} d_i & \text{if } \sum_{k=1}^M R_k V_{ik} + \sum_{j=1}^N \pi_{ji} p_j^* + e_i \geq d_i \\ \sum_{k=1}^M R_k V_{ik} + \sum_{j=1}^N \pi_{ji} p_j^* + e_i & \text{if } d_i > \sum_{k=1}^M R_k V_{ik} + \sum_{j=1}^N \pi_{ji} p_j^* + e_i \geq 0 \\ 0 & \text{if } \sum_{k=1}^M R_k V_{ik} + \sum_{j=1}^N \pi_{ji} p_j^* + e_i < 0 \end{cases}$$

This payment vector  $p_i^*$  is used to represent total interbank payments made by bank  $i$  to the rest of the banking system under the clearing mechanism. It has limited liability and proportional sharing in case of bankruptcy.

Using this payment vector, we can easily identify the insolvent banks in the system if  $p_i^* < d_i$ . In that case, the recovery rate will be  $(p_i^* / d_i)$ . More specifically speaking, a bank defaults and becomes insolvent if  $\sum_{k=1}^M R_k V_{ik} + \sum_{j=1}^N \pi_{ji} p_j^* + e_i - d_i < 0$ .

A contagious default may happen on Bank  $i$  in one of the two following scenarios:

- One or more banks are not be able to keep their payment promises to Bank  $i$ , causing  $i$ 's insolvency. Using our model to explain, that is  $\sum_{k=1}^M R_k V_{ik} + \sum_{j=1}^N \pi_{ji} d_j + e_i - d_i \geq 0$ , but  $\sum_{k=1}^M R_k V_{ik} + \sum_{j=1}^N \pi_{ji} p_j^* + e_i - d_i < 0$ .
- The defaults of one or more correlated financial products in bank  $i$ 's portfolio can reduce the portfolio value  $b_i$ . At the same time, they can also reduce the payment abilities of banks that have obligations to  $i$ . Together these two effects may cause bank  $i$  become insolvent. i.e.,  $\sum_{k=1}^M R_k V_{ik} + \sum_{j=1}^N \pi_{ji} d_j + e_i - d_i \geq 0$ , but  $\sum_{k=1}^M R_k' V_{ik} + \sum_{j=1}^N \pi_{ji} p_j^* + e_i - d_i < 0$ , where  $R_k'$  denotes the market closing price of financial product  $k$  that become default.

To summarize, this model of the banking system is developed for simulating the contagious defaults of banks under various stress scenarios and how our ranking algorithm can help reduce systemic risk in the bank network. In addition, the design of the ranking algorithm has also utilized representations developed in this model.

## A Network-based Algorithm for Ranking Systemic Risks

Existing risk management research focused on econometric analysis of market and credit risks. Although there are several studies taking a network perspective to study the systemic risks in the banking systems (Eisenberg and Noe 2001; Elsinger et al. 2006; Markose et al. 2010; May and Arinaminpathy 2010), no effective mechanisms or algorithms have been proposed to measure and manage such risks. In this study, we developed a algorithm that is based on the famous HITS algorithm (Kleinberg 1999) to rank systemic risks for each bank and financial product in the bank network. Although the HITS algorithm is initially designed to measure the importance of web pages in the densely interconnected World Wide Web, the underlying mechanism can be applied in many other domains. The importance (of a web page) is a characteristic that cannot be directly measured. HITS algorithm is essentially using the links a web page received from other web pages to quantify and measure its importance. The assumption is that, if a web page A provides a hyperlink that connects to web page B, A is actually offering its recognition to enhance the importance of web page B through this hyperlink. Therefore, the authority score of the web page A calculated using HITS is actually measuring the overall impacts of recognitions offered by all web pages that links to A. The hub score is measuring the overall impacts of recognitions A offered to the web pages it links to.

We developed a network-based algorithm using the same underlying mechanism of HITS algorithm to measure and then rank the systemic risks associated with banks mainly for three reasons Firstly, like importance of web pages, the systemic risk associated with banks cannot be quantified and directly measured. Secondly, the systemic risk associated with a bank is a type of exogenous risk that originates from the possible defaults of banks that have interbank payment obligations with A and also from the financial products owned by A. Thirdly, the systemic risks mainly exists in a densely connected bank network and their impacts are mainly transmitted through the interbank payment relationships and the ownership (with financial products) relationships.

We modified HITS algorithm to rank systemic risks in bank networks which are significantly different from ranking web page importance. First, there are two types of nodes in the bank network – banks and financial products. Thus we need to calculate both authority and hub scores for these two types of nodes. Second, since the possible defaults of financial products may cause the insolvency of banks, not the other way around, the financial product nodes only have out-links. Accordingly, in our algorithm, financial product nodes will only have hub scores. On the other hand, the default of banks may cause the insolvency of each other through interbank payment links. Therefore, bank nodes will have both in and out- links, along with the authority and hub scores.

### Measuring Systemic Risk Associated with Financial Product Nodes

We firstly aim to measure the systemic risk associated with the financial product nodes from the banks' perspective. We mainly focused on two factors:

- The likelihood of the default of a financial product owned by a bank  $i$ . This is often linked to rating scores provided by credit agencies. We denote the probability of the default of a financial product  $k$  as  $f_k$  ( $k \in M$ ).

- The total impacts/losses caused by the default of a financial product  $k$  on its owner bank  $i$ . We denote that using  $\Delta R_k V_{ik} / p_i^*$ , where  $\Delta R_k$  is the change in the price of the product  $k$  caused by the default event.

Together these two factors determine the expected impacts (possible loss) of the default of a financial product  $k$  on its owner bank  $i$  as  $f_k(\Delta R_k V_{ik} / p_i^*)$ .

### Measuring Systemic Risk Associated with Interbank Payments

Then we aim to measure the systemic risks associated with the interbank payments in the bank network. We propose  $IP_{ij}$  as a measure of the expected impacts (possible loss) caused by the default of an individual bank  $i$  on one of its debtor banks  $j$  through the interbank payment links. That is

$$IP_{ij} = C(l_{ij} / p_j^*),$$

where  $C$  is the average default rate for all banks in the bank network during a certain time period.

### Ranking Algorithm Design

We then introduce the design our network-based ranking algorithm. Similar to HITS, our algorithm has an iterative process to update both hub score and authority score for the two types of nodes. One thing to note is that financial product nodes only have out-links while bank nodes have both in- and out-links. Thus the financial product nodes only have hub scores (FPHUB) and bank nodes have both authority (BANKAU) and hub scores (BANKHUB).

- In the initial step, for each bank  $i$ , we calculate the coefficient for the hub score of the financial product  $k$  it owns as  $\alpha_{ki} = f_k(\Delta R_k V_{ki} / p_i^*)$  as explained in the previous section. Then we set the coefficient for the bank  $i$ 's hub score to bank  $j$  as  $\beta_{ij} = IP_{ij} = C(l_{ij} / p_j^*)$ . In this step, we are weighting the in-links of bank nodes based on the expected impacts of the two sources for these links.
- Second, we start to update bank  $i$ 's authority score  $BANKAU_i$  as:

$$BANKAU_i = \sum_{k \in M} \alpha_{ki} FPHUB_k + \sum_{j \in N} \beta_{ji} BANKHUB_j \quad (1)$$

where  $M$  is the set of financial product owned by bank  $i$ , and  $N$  is the set of banks that have payment obligations to  $i$ . Similar to the HITS algorithm, initially both FPHUB and BANKHUB are set to one. This update process means that the authority score that rank bank  $i$ 's systemic risk is from the systemic risks associated with  $i$ 's portfolio of financial products, and all the banks that may affect  $i$ 's cash flow through possible defaults of interbank payments. The coefficients are the possible impacts of these two systemic risk sources on bank  $i$ .

- Third, we update financial product  $k$ 's hub score as  $FPHUB_k$ . This score represents the overall systemic risk financial product  $k$  may has (the possible loss of its default) on the whole bank network/system through its owner banks. Therefore, it is calculated as

$$FPHUB_k = \sum_{j \in H} S_{jk} BANKAU_j \quad (2)$$

where  $S_{jk}$  is the percentage of the product  $k$  held by bank  $j$ ,  $H$  is the set of banks that hold  $k$ .

- Fourth, we update Bank  $i$ 's hub score as  $BANKHUB_i$ . This score represents Bank  $i$ 's systemic risk (the possible loss of its default) on the whole bank network through the banks it has payment obligations. Therefore, it is calculated as

$$BANKHUB_i = \sum_{j \in N'} OP_{ji} BANKAU_j \quad (3)$$



where  $OP_{ji}$  is the percentage of the bank  $j$ 's total incoming payments bank  $i$ 's payment occupies, and  $N'$  is the set of banks that  $i$  has payment obligations.

One thing to note is that for each iteration of this algorithm we normalize these three scores like the original HITS algorithm does. Then we repeatedly execute the three steps until these three scores converge. The convergence proof of our algorithm is similar with the proof for the weighted HITS algorithm in Bharat and Henzinger's paper (1998). To explain this proof, we first unify the representations of bank nodes and financial product nodes by denoting  $AU = [BANKAU, 0]$  and  $HUB = [BANKHUB, FPHUB]$  as the unified authority score and hub score

vector, respectively. Then the authority-weight matrix of our algorithm is  $AW = \begin{bmatrix} B' & A \\ 0 & 0 \end{bmatrix}$ , where  $B_{ij} = \beta_{ij}$

and  $A_{ij} = \alpha_{ij}$  in formula (1) and  $B'$  is the transpose of matrix  $B$ . The computation of the authority score can be

written as  $AU = AW * HUB$ . Similarly, the hub-weight matrix is  $HW = \begin{bmatrix} OP' & 0 \\ S & 0 \end{bmatrix}$  and the computation of

the hub score can be written as  $HUB = HW * AU$ . We define  $D = HW * AW = \begin{bmatrix} OP' * B' & OP' * A \\ S * B' & S * A \end{bmatrix}$  in

which all entries are positive. Following the Lemma 1 in (Bharat et al. 1998), after  $i$  iterations, the hub score vector  $HUB$  which equals to  $D^i * Z$  will converge (Golub and Van Loan 1996), where  $Z$  is a vector with each coordinate equal to 1. The authority score will converge for the same reason. The converged hub scores for each financial product and bank are our ranking scores for measuring their systemic risks.

## Evaluation of the Proposed Algorithm through Simulation

To assess the effectiveness of this network-based ranking algorithm, we first plan to use a simulation approach to generate stress scenarios in which the bank network undergoes various types of major economic shocks. We also simulate how the contagious bank failures happen through the two sources of systemic risks modeled previously. In this simulation, it is assumed that there are two time points:  $t = 0$ , the observation day, and  $t = 1$ , the payment clearing date, when all interbank payments are settled according to the clearing vector  $p^*$  we defined before. At  $t = 0$ , the portfolio holdings of financial products  $b$  for each bank are observed. In addition, the interbank payments among banks are modeled as a  $N \times N$  matrix  $L$ . The remaining value of bank assets is represented as  $e$ . Both the values of  $b$  and  $e$  is exposed to various market and credit risk such as the sudden drop of prices for major financial products banks held. According the clearing payment vector  $p^*$  defined before, the value of  $p^*$  depends on the realization of such risk factors. To generate a stress scenario, we draw a realization of these risk factors using real-world data such as interest rates and currency exchange rates, and revalue  $b$  and  $e$  for each bank to estimate its new value of  $p^*$ .

After generating various possible scenarios of contagious defaults of banks, we focus on evaluating the effectiveness of our proposed ranking algorithm. We will apply this algorithm to the data in each generated scenario for calculating and ranking the systemic risks associate with each bank and financial product. The output is a list of ranked banks and financial products based on the level of systemic risks they have. We then devise strategies based on this list to reduce the systemic risk in the bank network (e.g., prevent banks to purchase financial products with high systemic risk). We then compare the number and the rate of default banks (caused by contagious failures) between the original scenario and the one which use the algorithm to mitigate the systemic risks. For multiple scenarios, if the numbers of default banks in original scenarios are consistently and significantly larger than the ones in the scenarios that adopted our ranking algorithm. Then the algorithm will be proven to be effective in reducing systemic risks in bank networks.

## Dataset

In this study, we plan to use data from the Bank Regulatory and the Bank Holding Companies Databases in the Wharton Research Data Services (WRDS). The Bank Regulatory Database contains accounting data for bank holding companies, commercial banks, savings banks, and savings and loans institutions. The source data is from the required regulatory forms filed for supervising purposes. The Bank Holding Companies Database collects financial data included in the FRY-9 reports which contain balance sheet, income information, risk-based capital measures and additional supporting schedules. The information in these two databases is mainly used to generate stress scenarios in our simulations of contagious failures in bank networks.

## Discussion and Future Work

In summary, we developed a network-based ranking algorithm to rank systemic risk associated with banks and financial products in the bank networks. In addition, we extended Elsinger's (2006) model of the banking system and plan to adopt it on real world banking data to simulate the effects of our proposed algorithm in reducing systemic risk (contagious failures) in the bank network. Our proposed research has both theoretical and practical contributions. Theoretically, it contributes to the research that aims to discover the causes and mechanisms of contagious bank failures in bank networks. It provides a novel network perspective for researchers to study how system-wide bank failures happen caused by the failures of several key banks or a market freeze. Empirically, our study intend to provide a network-based ranking mechanism for systemic risk associated with banks and financial products, aiming to help stakeholders in the banking industry to devise effective strategies for reducing such systemic risk. The long term goal is to prevent system-wide breakdown in the banking system by identifying banks and financial products with high systemic risk and reducing such risk before total meltdown.

Our future work consists of three parts. First, we need to collect data from the Bank Regulatory and the Bank Holding Companies Databases in WRDS. Second, we will construct the bank network and generate various stress scenarios for the banking system. Third, we then compare the numbers of contagious bank failures in original scenarios and in scenarios that adopted our proposed network-based algorithm for systemic risk mitigation. We believe our algorithm offers a new way to estimate systemic risk (contagious bank failures) in a bank network under various stress scenarios.

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